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Article

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Chess Endgame News: an Endgame Challenge for Neural Nets

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It is an exciting time for computer chess. One might have thought that things were plateauing out because even cloud-supported engines such as STOCKFISH are ELO-advancing only slowly. But then, along comes an exciting new, non-Shannon (1950) paradigm. David Silver's (2018) Deep Mind team successfully combine the ideas of neural-network-based learning and Monte-Carlo Tree Search in ALPHAZERO to find new competences in Go, Chess (Sadler and Regan, 2019) and Shogi.

Here, I pick out just three interesting aspects of this advance. First, ALPHAZERO is self-taught, an attractive minimalism providing maximum independence from suboptimal human ways of thinking. We first saw the benefits of this with the ATARI 2600's Breakout and other games (Mnih et al, 2013). Secondly, Deep Mind's openness has facilitated the creation by others of similar engines such as Go-engine LEELAZERO and chess engine 'LC0' LEELA CHESS ZERO. Thirdly, the ALLIESTEIN hybrid engine for one is coming to the fore, aiming to synergise Shannon and MCTS approaches.

However, both LC0 and ALLIESTEIN seem weak, even rudderless, in the endgame. It is worth quoting Polya (1962): "If you can't solve a problem, then there is an easier problem you can solve: find it." Perhaps it is appropriate here to define a challenge for the deep-learning community, a research mini-manifesto as it were. Train neural-networks on specific chess endgames (Haworth and Velliste, 1998) and benchmark their efficacy against the existing sub-8-man tables. How well will they play? Can we infer higher-order rules and guidelines for play from them?

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